Health Informatics

Lecture 1: Introduction

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About me: Samantha Kleinberg

- PhD in CS
- Have worked in biomathematics, bioinformatics/computational biology, biomedical informatics
- Current research
  - Time series data, causal inference
  - Mobile health
  - Decision-making

CUMC Neuro-ICU

NICU dataset

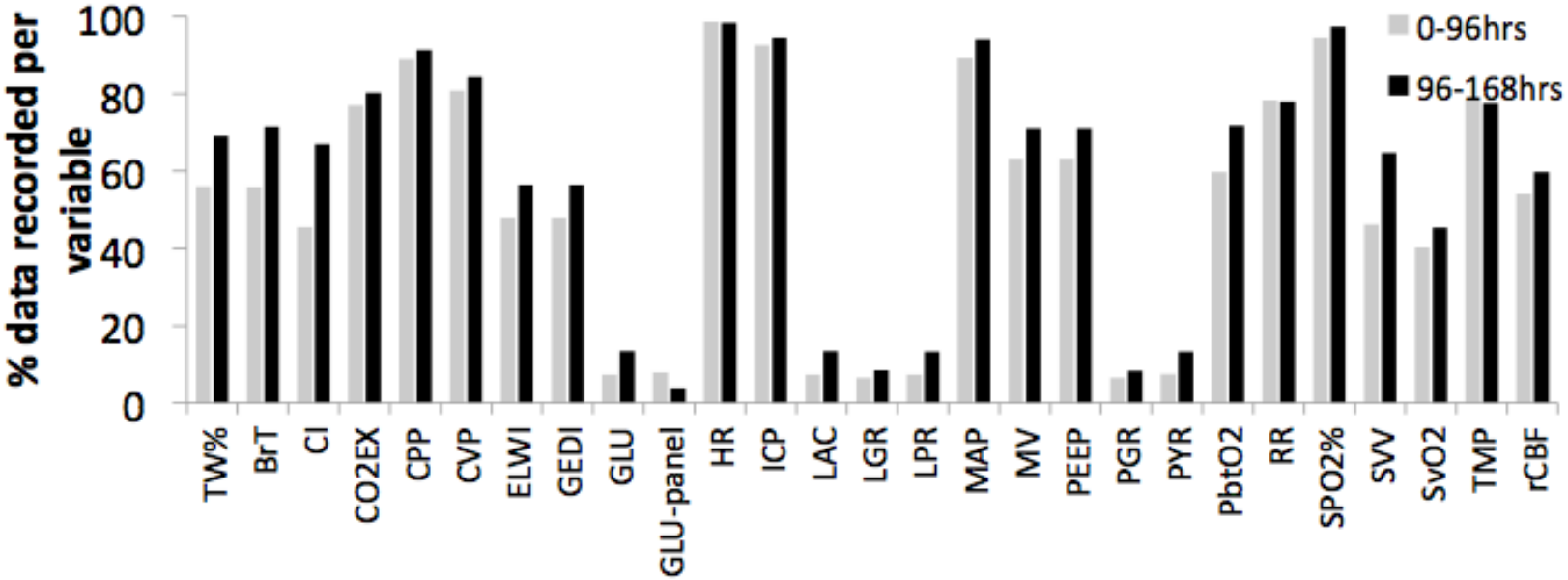
- 98 patients with subarachnoid hemorrhage

- Monitoring included
  - Depth and surface EEG
  - Microdialysis
  - Physiologic measurements

(no data on procedures)

Lots of data, but lots of missing data

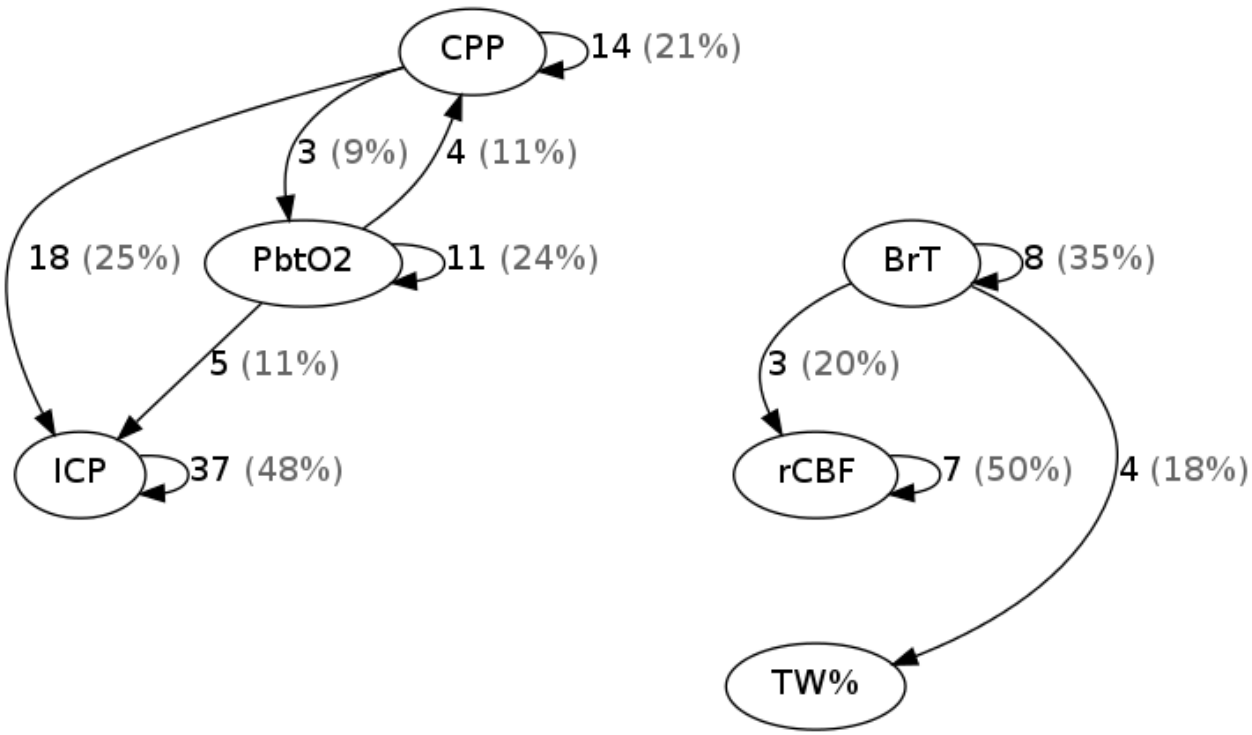
- Device malfunctions
- Device connected to perform a procedure



And…

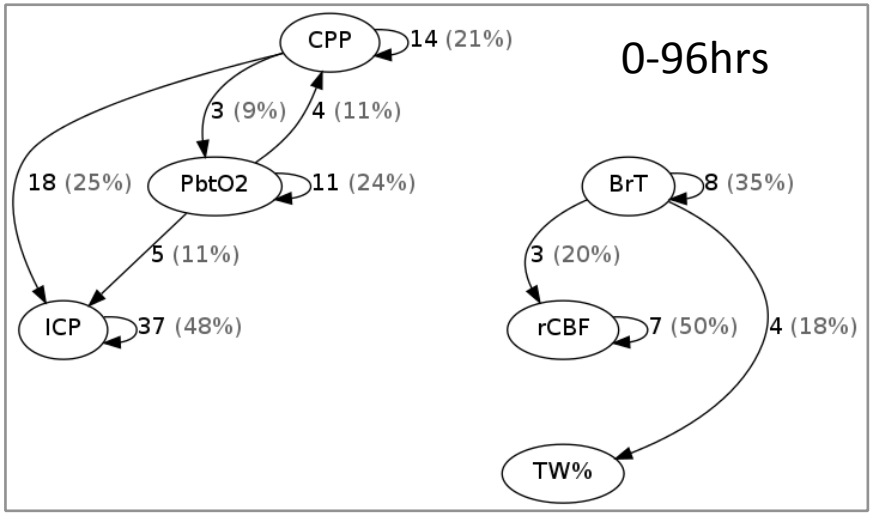
- All variables may be missing at once (if measured by single device)
  - Can't use imputation methods that assume some present values
- Missing values depend on variable + other variables
  - e.g. BG depends on itself, as well as insulin
- Variables are correlated across time

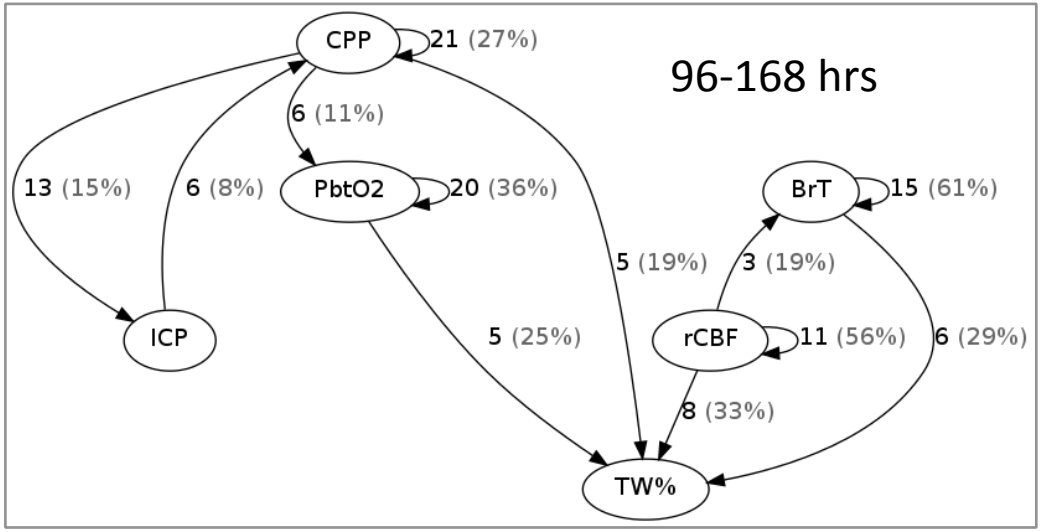
Different data, different physiology

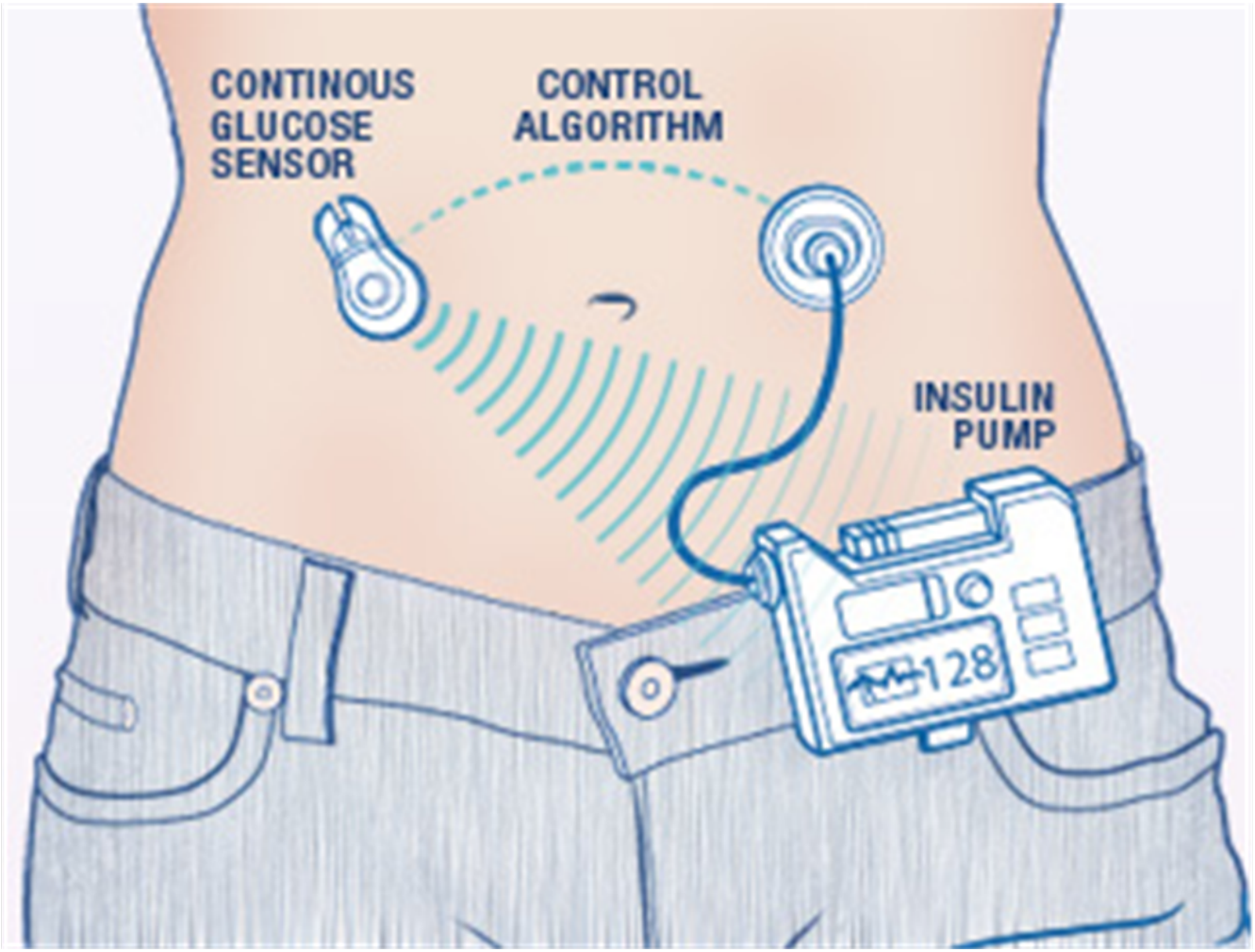


Claassen J, Rahman SA, Huang Y, Frey H, Schmidt M, Albers D, Falo CM, Park S, Agarwal S, Connolly ES, Kleinberg S (2016) Causal structure of brain physiology after brain injury. PLoS ONE.

Regulation changes over time







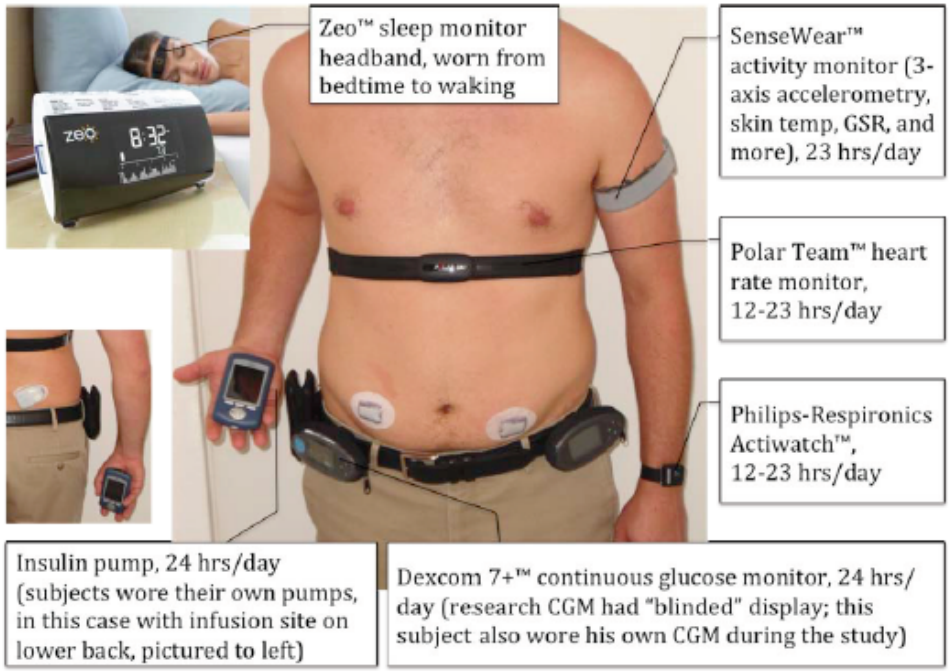
http://discoverysedge.mayo.edu/artificial-pancreas/

Causes of changes in glucose

Cohort: 17 subjects with T1DM

Sensor data (collected for >72 hours)

- Glucose values
- Insulin dosage
- Activity
- Sleep stage
- Heart rate
- Temperature



With N. Heintzman (UCSD) http://dial.ucsd.edu/what-we-do.php

Results

very vigorous exercise leads to hyperglycemia (fdr <.01) in 5-30 minutes

- Found using both HR (anaerobic activity zone) and METs

- Not found with strict discretization
- Supported by literature (Marliss and Vranic, 2002; Riddell and Perkins, 2006)

S. Kleinberg and N. Heintzman. Using uncertain data from body-worn sensors to gain insight into type 1 diabetes. Journal of Biomedical Informatics, 2016.

Why are you here?

Why health informatics?

https://www.nih.gov/AllofUs-Research-Program

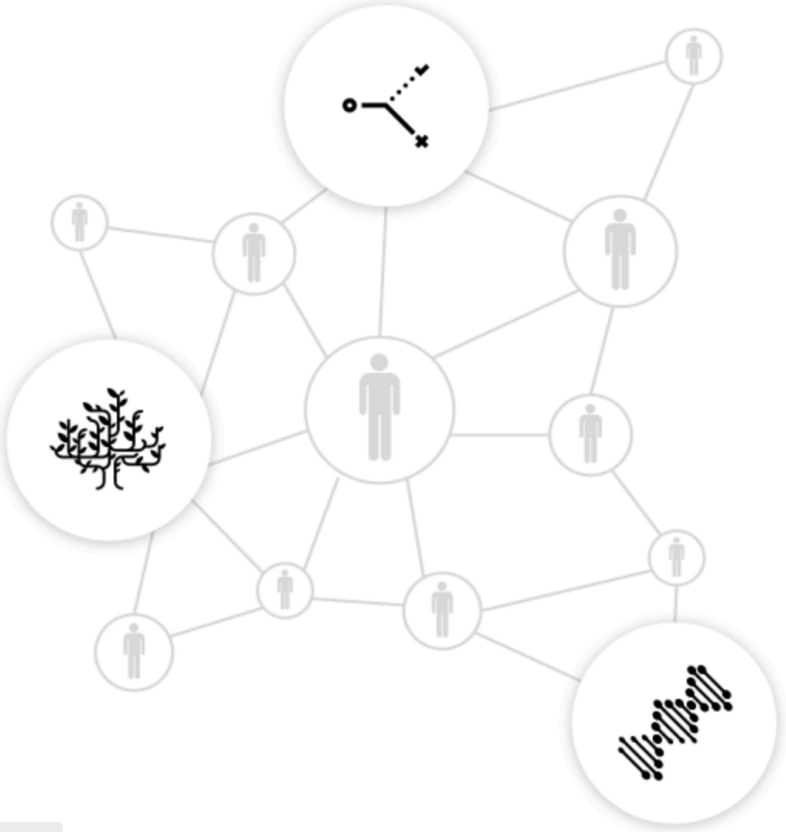
WHAT ARE THE GOALS?

Engage a group of **1 million or more U.S. research participants** who will share biological samples, genetic data and diet/lifestyle information, all linked to their electronic health records. This data will allow researchers to develop more precise treatments for **many diseases and conditions**.

Pioneer a new model of research that emphasizes **engaged research participants, responsible data sharing and privacy protection.**

THE HUMAN PROJECT
A KAVLI FOUNDATION INITIATIVE

ABOUT PEOPLE RESEARCH GOVERNANCE EVENTS PRESS



a menu

Take Control of Your Data

You already shed data through time and space all day long, collected by the corporations that track your spending, location, and use of technology. We at The HUMAN Project believe that the people's data can be better used to serve them, their communities, and society.

What Will We Do?

We will study the lives of 10,000 New York City residents in approximately 4,000 households over the span of decades by collecting measurements across multiple domains and disciplines, and provide this massive, interdisciplinary, and secure dataset to the research community to achieve previously unattainable groundbreaking advancements in medicine, the social sciences, and understanding the true nature of human behavior, while fostering evidenced-based public policies.

Why Now?

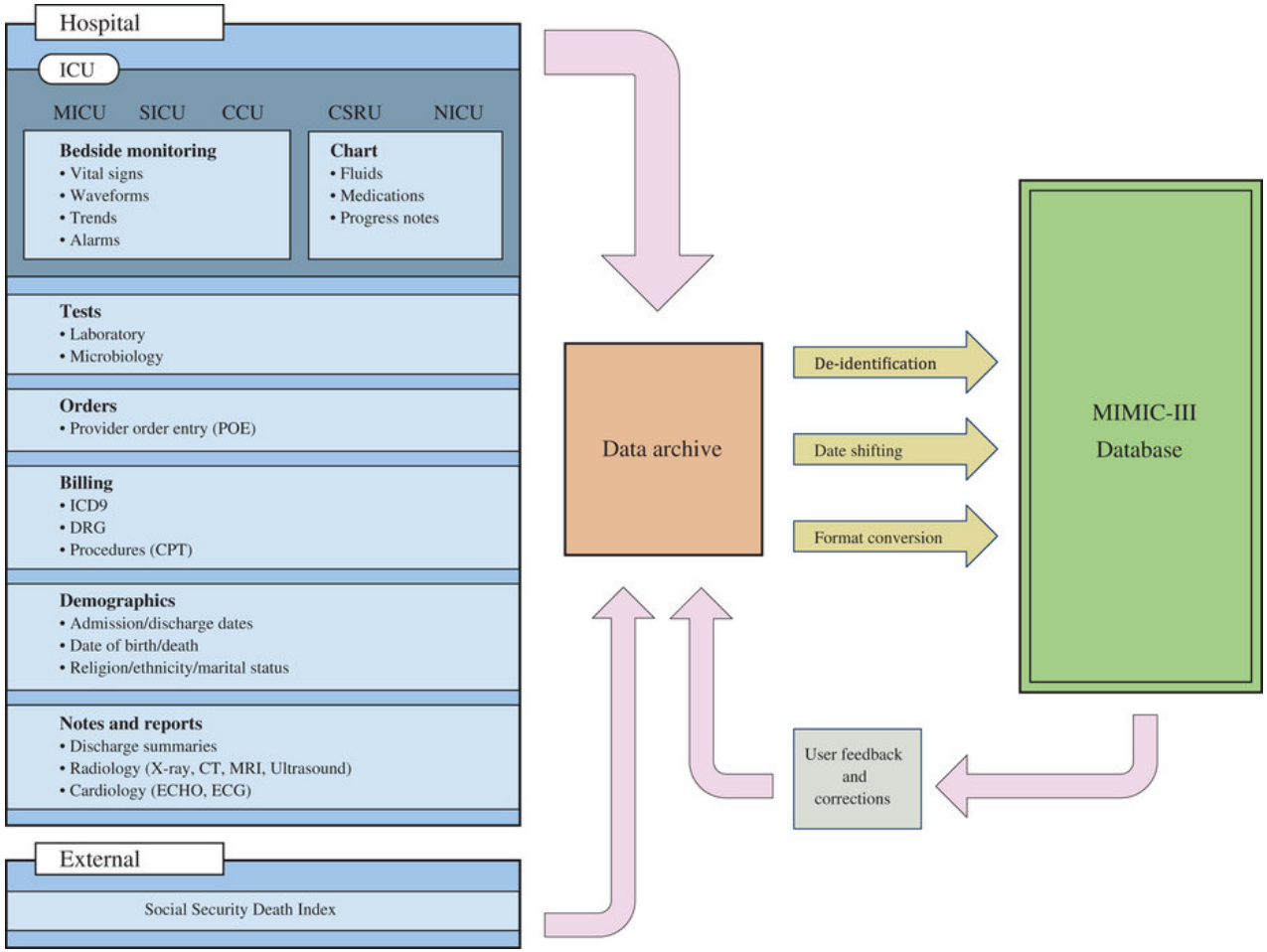
Enrollment starting early 2018

And for final projects

If you use MIMIC data or code in your work, please cite the following publication:

MIMIC-III, a freely accessible critical care database. Johnson AEW, Pollard TJ, Shen L, Lehman L, Feng M, Ghassemi M, Moody B, Szolovits P, Celi LA, and Mark RG. Scientific Data (2016). DOI: 10.1038/sdata.2016.35.
Available from: http://www.nature.com/articles/sdata201635

https://mimic.physionet.org



Johnson, A. E. W. *et al.* MIMIC-III, a freely accessible critical care database. *Sci. Data* 3:160035 doi: 10.1038/sdata.2016.35 (2016).

Example projects

- Do patients with diabetes with more hospital admissions have more amputations?
- Comparing drug overdose trends to national statistics
- Classification of pneumonia using waveform data
- Difference in ICU stay duration for CHF in T1D vs T2D patients
- Visualization of patient clusters

What could we do with this?

- Who’s the user?
- What problem do they have?
- How can CS help?

But what do we need to know first?

- What's the data actually? Is it correct?
- Can we really apply ML/DM methods to it? What are the challenges?
- Can we share data freely? Why not?
- How do we preserve privacy

(and much more)

Syllabus

CS 544, Spring 2018

HEALTH INFORMATICS

From medical centers and individual physicians adopting electronic medical records, to patients keeping track of chronic diseases through websites and apps, we live in an era of unprecedented access to health data. These data enable inference of drug side effects, causes of disease, and new treatments, but the new terminologies, policies, and challenges in understanding the data itself can make it difficult for computational researchers to apply their techniques to this new area and for health professionals to begin using informatics to solve practical problems. This course will give both groups the foundation needed to propose, evaluate and develop projects such as secondary analysis of health data and will enable them to begin effective interdisciplinary collaborations. Students will learn how health data is collected (in both hospital and non-hospital settings), how the structure of record systems impacts the research process and interpretation of results, and how to design and evaluate studies involving secondary use of health data (while complying with HIPAA and IRB regulations) in order to gain new medical knowledge and improve healthcare delivery.

Prerequisites None. The course is intended for advanced undergraduate and graduate students from computer science and other disciplines.

Text There is no required textbook. Readings are articles that will be provided.

Evaluation Discussion of the readings is an important part of the course and will count towards the final grade. It is not possible to succeed in this course without participating. There will be a final project (and presentation), as well as one presentation for the journal club assignment and discussions of case studies.

Grades will be: 10% homework, 15% participation, 25% midterm exam, 50% final project.

Syllabus (continued)

CS 544, Spring 2018

Schedule

Below is the weekly schedule of topics, readings for each session, and deadlines. All journal articles will be available electronically through the library or in Canvas. Readings may change, but in that case an announcement will be made in class.

1/22 Introduction to health informatics. Overview of field, relation to bioinformatics

1/29 Where and why is health data collected? (including meaningful use and PPACA). Including claims data, clinician-generated data, and information exchange.
- P. Wicks, T. E. Vaughan, M. P. Massagli, and J. Heywood. Accelerated clinical discovery using self-reported patient data collected online and a patient-matching algorithm. *Nature biotechnology*, 29(5):411–414, 2011 [pdf]

2/5 What are the data? EMRs, PHRs, and data standards (narrative vs. structured data, ontologies)
- S. Abhyankar, D. Demner-Fushman, F. M. Callaghan, and C. J. McDonald. Combining structured and unstructured data to identify a cohort of icu patients who received dialysis. *Journal of the American Medical Informatics Association*, 1 2014 [pdf]

2/12 Ethics in biomedical research. HIPAA, IRBs, and de-identification. We will discuss the rules and regulations governing health research and, from a practical standpoint, how to preserve privacy when conducting research
- E. Vayena, R. Brownsword, S. J. Edwards, B. Greshake, J. P. Kahn, N. Ladher, J. Montgomery, D. O'connor, O. O'neill, M. P. Richards, et al. Research led by participants: a new social contract for a new kind of research. *Journal of medical ethics*, 2015 [html]

2/21 Data reuse and evaluation challenges (what is a diagnosis really?)
- S. Kleinberg and N. Elhadad. Lessons learned in replicating data-driven experiments in multiple medical systems and patient populations. In *AMIA Annual Symposium*, 2013 [pdf]
- IRB proposals due

2/26 Research with EMR data, Introduction to MIMIC dataset
- F. Doshi-Velez, Y. Ge, and I. Kohane. Comorbidity clusters in autism spectrum disorders: an electronic health record time-series analysis. *Pediatrics*, 133, 2014 [pdf]

3/5 Midterm exam

3/19 Methods for evaluation. How can we compare systems and determine if a project is successful?

- M. Ghassemi, J. Marshall, N. Singh, D. J. Stone, and L. A. Celi. Leveraging a critical care database: selective serotonin reuptake inhibitor use prior to icu admission is associated with increased hospital mortality. *CHEST Journal*, 145(4):745–752, 2014 [html]

- Project proposals due

3/26 Pharmacovigilance and drug discovery

- R. W. White, N. P. Tatonetti, N. H. Shah, R. B. Altman, and E. Horvitz. Web-scale pharmacovigilance: listening to signals from the crowd. *Journal of the American Medical Informatics Association*, 2013 [pdf]

4/2 Journal club discussion of recent papers in health informatics

4/9 Decision Support

- P. J. O'Connor, J. M. Sperl-Hillen, W. A. Rush, P. E. Johnson, G. H. Amundson, S. E. Asche, H. L. Ekstrom, and T. P. Gilmer. Impact of electronic health record clinical decision support on diabetes care: a randomized trial. *The Annals of Family Medicine*, 9(1):12–21, 2011 [pdf]

4/16 Public health, epidemiology, and mobile health

- M. Rabbi, M. H. Aung, M. Zhang, and T. Choudhury. Mybehavior: automatic personalized health feedback from user behaviors and preferences using smartphones. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, pages 707–718. ACM, 2015 [pdf]

4/23 Presentations of final projects

- Written project reports due

4/30 Presentations of final projects

Administrativia

- Course website: http://www.skleinberg.org/teaching/HI18/
- Prerequisites: none
- Textbook: **none**, articles
- Everything on syllabus CAN CHANGE (will make announcement in class)
- Workload/grading:

  midterm presentation (25%), final project (50%), participation (15%), homework (10%)

  – Participation includes weekly reading discussions

Key policies

1. No late work. There are few deadlines, but if the deadline's 11:59pm, work submitted at 12:01am isn't accepted.

   Do not email me saying the time changed as you were submitting. That is the definition of late.

   Why? Try submitting an NIH grant or conference paper 2 minutes late!

2. Plagiarism = F

What's plagiarism?

Presenting someone else's work as your own

- Copying an entire paper
- Copying parts of other works, without attribution
  - E.g. quotes without citations, images
- Changing a few words, but keeping ideas and structure, without acknowledging source

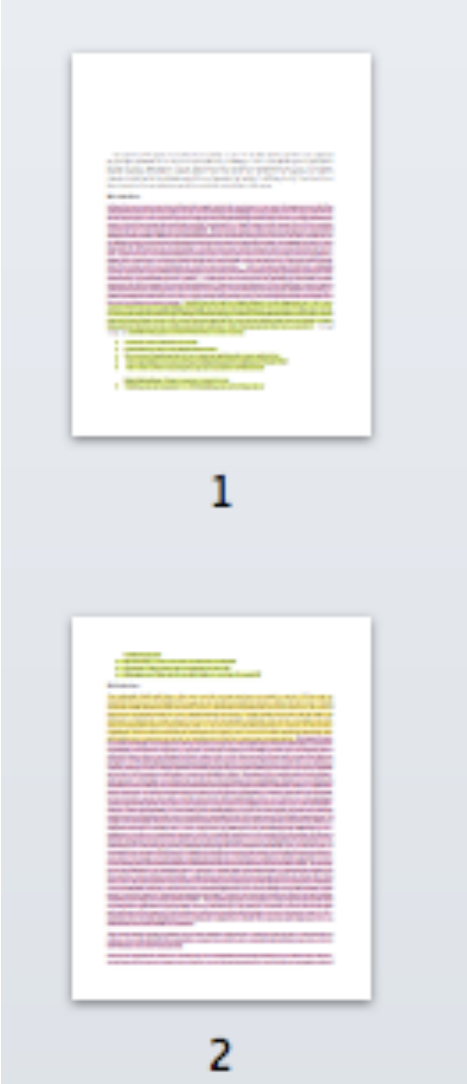
Easy to avoid! Do your own work and acknowledge all sources. Quotes must be in quotes. Don't submit a collage.

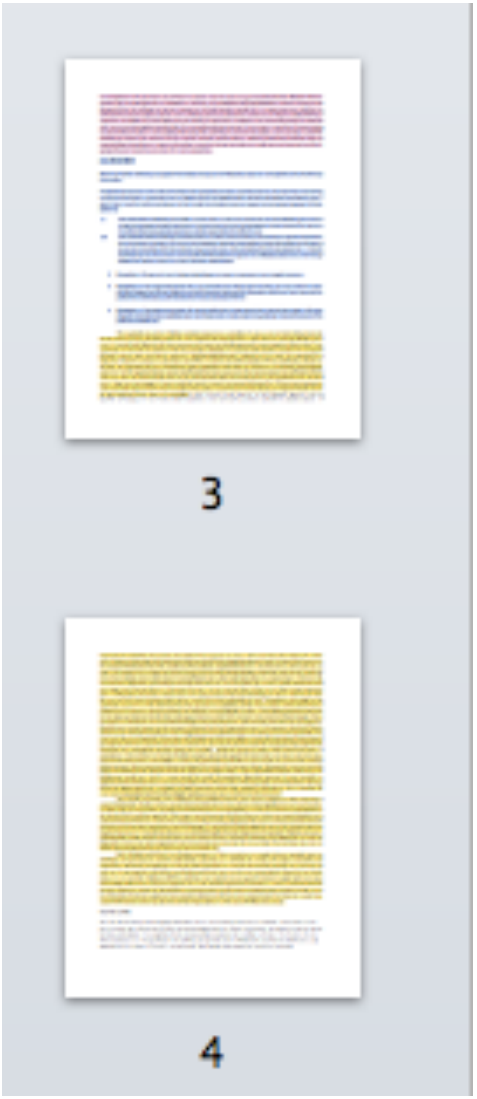
1. Quotes belong in quotation marks

- WRONG!
  - Blah blah. Text from other papers. Blah Blah. [Citation]
  - **Section 1** [Citation]. Text you did not write.
  - **Section 1** [Full text of someone else's paper] **References** Else, Someone. "Paper you copied from"

- Right ☺
  - My text "Quote from awesome work." [citation] my text

2. Papers aren’t collages





Seriously, papers are not collages

- “But the other paper said what I wanted to!”
  - Put it in your own words
- “It’s just reference material”
  - Then add a reference to it
- “I copied from your book because you said it so well!”
  - I am not senile and will recognize my own words

3. No copying/close paraphrasing

Don't Let This Be You!

2006: Kaavya Viswanathan, Harvard sophomore, 2-book deal from Little, Brown

Plagiarized!

Sloppy Firsts (2001), page 7: "Bridget is my age and lives across the street. For the first twelve years of my life, these qualifications were all I needed in a best friend. But that was before Bridget's braces came off and her boyfriend Burke got on, before Hope and I met in our seventh grade Honors classes" (McCafferty, quoted in Zhou, "Examples…").

Opal Mehta (2006), page 14: "Priscilla was my age and lived two blocks away. **For the first** fifteen years of my life**, those were the only qualifications I needed in a best friend**. … **But that was before** freshman year, when Priscilla's glasses **came off**, and the first in a long string of boyfriends **got on**" (Viswanathan, quoted in Zhou, "Examples…").

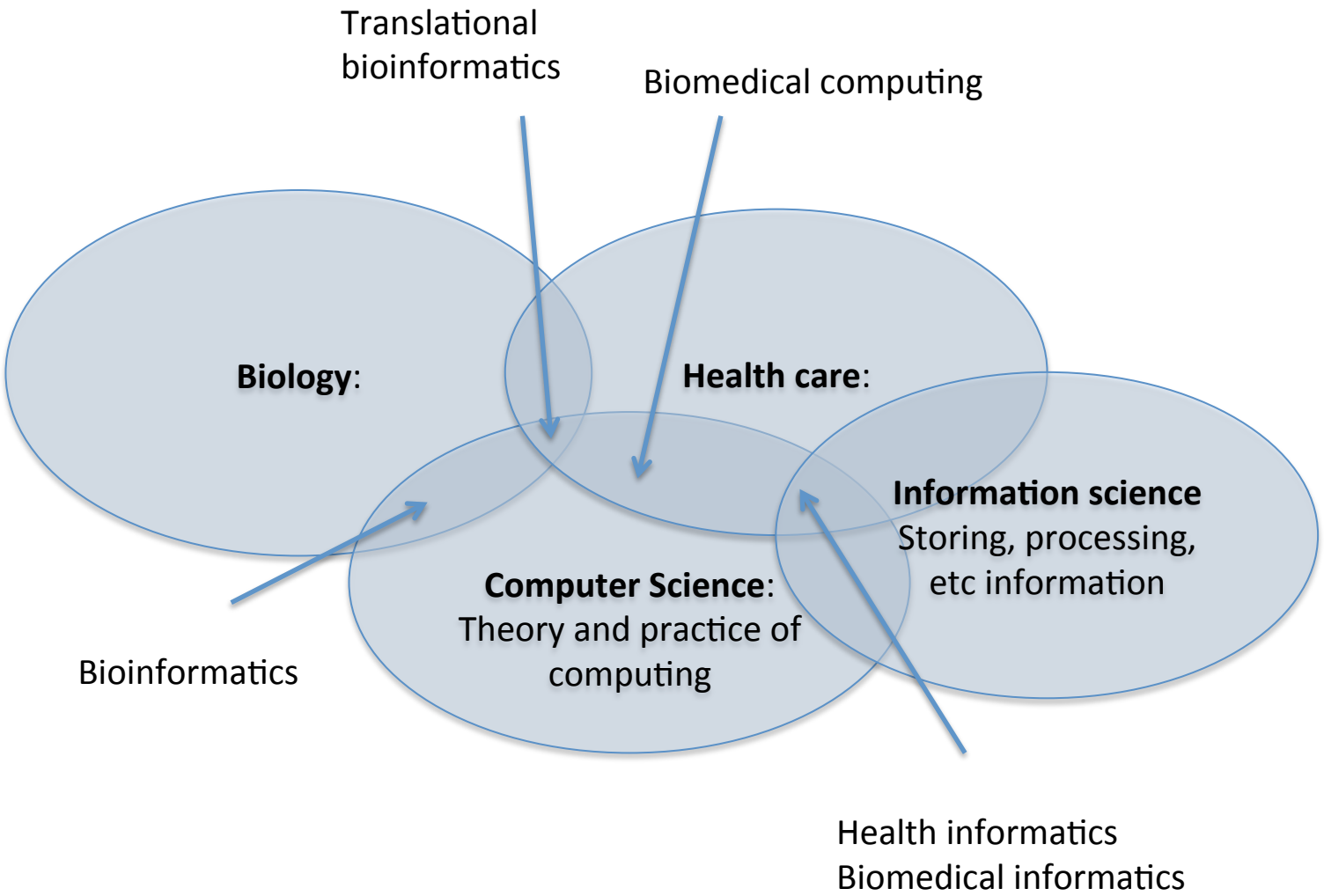
"an act of literary identity theft"
(Steve Ross, qtd. in Zhou, "Publisher…")

http://researchguides.stevens.edu/plagiarism

If you're having trouble…

- Come to office hours! Monday 2-3 in North 208 and by appointment
- Email me
- Email or meet with CA Ivan Ching (iching@stevens.edu)

What’s health informatics?


Translational bioinformatics
Biomedical computing
Biology:
Health care:
Information science
Storing, processing, etc information
Computer Science:
Theory and practice of computing
Bioinformatics
Health informatics
Biomedical informatics

Another definition

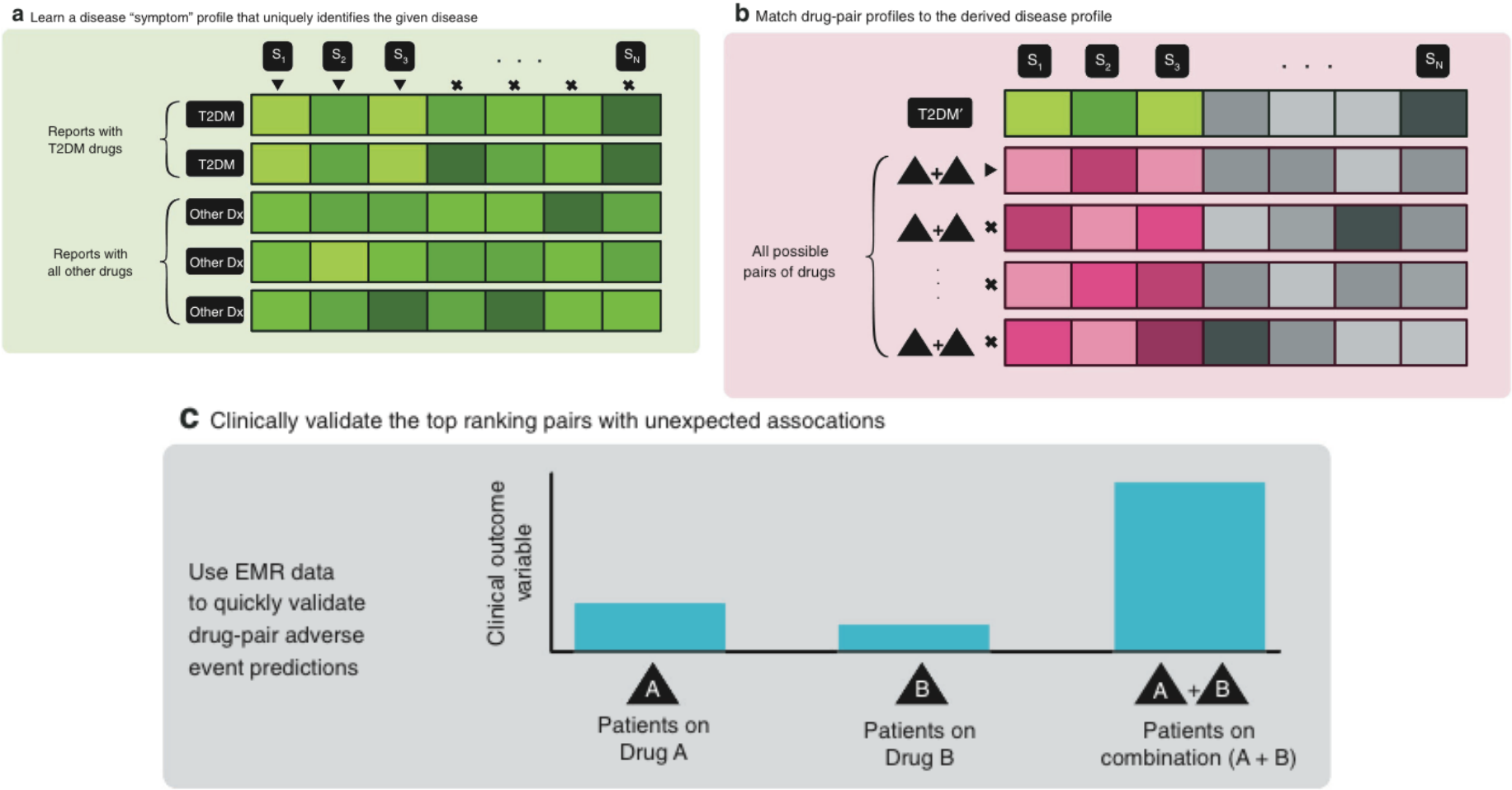
- **Definition**: Biomedical informatics (BMI) is the interdisciplinary field that studies and pursues the effective uses of biomedical data, information, and knowledge for scientific inquiry, problem solving, and decision making, driven by efforts to improve human health.
- **Scope and breadth of discipline:** BMI investigates and supports reasoning, modeling, simulation, experimentation, and translation across the spectrum from molecules to individuals and to populations, from biological to social systems, bridging basic and clinical research and practice and the healthcare enterprise.
- **Theory and methodology:** BMI develops, studies, and applies theories, methods, and processes for the generation, storage, retrieval, use, management, and sharing of biomedical data, information, and knowledge.
- **Technological approach:** BMI builds on and contributes to computer, telecommunication, and information sciences and technologies, emphasizing their application in biomedicine.
- **Human and social context:** BMI, recognizing that people are the ultimate users of biomedical information, draws upon the social and behavioral sciences to inform the design and evaluation of technical solutions, policies, and the evolution of economic, ethical, social, educational, and organizational systems.

Kulikowski, C.A., Shortliffe, E.H., Currie, L.M., Elkin, P.L., Hunter, L.E., Johnson, T.R., Kalet, I.J., Lenert, L.A., Musen, M.A., Ozbolt, J.G., Smith, J.W., Tarczy-Hornoch, P.Z. & Williamson, J.J., 2012, AMIA Board white paper: definition of biomedical informatics and specification of core competencies for graduate education in the discipline, *Journal of the American Medical Informatics Association*, pp. amiajnl-2012-001053

Main subfields

- (Translational) Bioinformatics
- Public health informatics
- Healthcare/Clinical informatics
- Consumer/mHealth

Example: Translational bioinformatics



Tatonetti, N.P., Denny, J.C., Murphy, S.N., Fernald, G.H., Krishnan, G., Castro, V., Yue, P., Tsau, P.S., Kohane, I., Roden, D.M. & Altman, R., 2011, Detecting drug interactions from adverse-event reports: interaction between paroxetine and pravastatin increases blood glucose levels, *Clinical Pharmacology & Therapeutics*, 90(1), pp. 133-42

Example: Public health Informatics

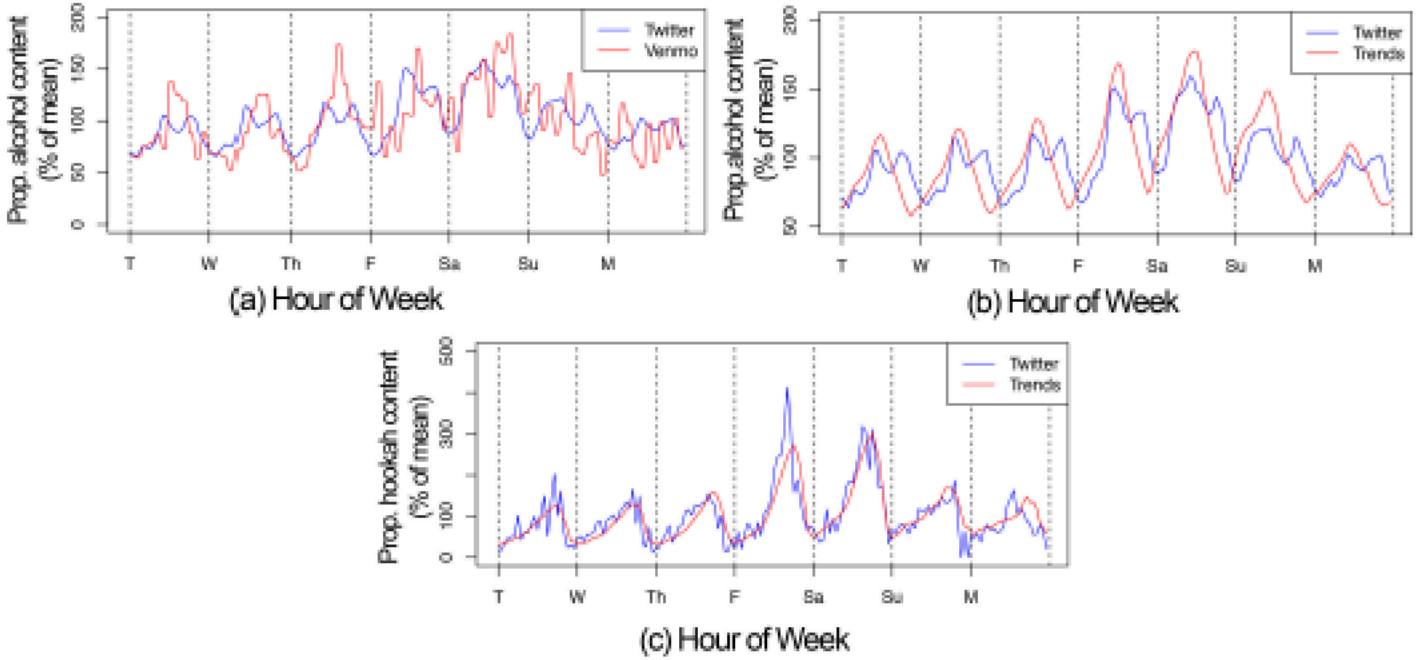


Fig. 5. Comparison of Twitter self-reports with (a) Venmo payments for alcohol (b) Google Trends for alcohol topics and (c) Google Trends for hookah topics. Dotted lines are at 8am. In (a) the Venmo data is at two-hour resolution for clarity. Venmo data is normalized by all transactions each hour, Google Trends are scaled based on proportion to all searches on all topics, and Twitter posts normalized to all Tweets from the API.

Tom Huang, Anas Elghafari, Kunal Relia, and Rumi Chunara. 2017. High-resolution Temporal Representations of Alcohol and Tobacco Behaviors from Social Media Data. Proc. ACM Hum.-Comput. Interact. 1, 2, Article 54 (November 2017), https://doi.org/10.1145/3134689

Example: Clinical informatics

Research and applications

OPEN ACCESS

Reduction in medication errors in hospitals due to adoption of computerized provider order entry systems

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Received 2 August 2012
Revised 19 December 2012
Accepted 10 January 2013
Published Online First 21 February 2013

ABSTRACT

Objective Medication errors in hospitals are common, expensive, and sometimes harmful to patients. This study's objective was to derive a nationally representative estimate of medication error reduction in hospitals attributable to electronic prescribing through computerized provider order entry (CPOE) systems.

Materials and methods We conducted a systematic literature review and applied random-effects meta-analytic techniques to derive a summary estimate of the effect of CPOE on medication errors. This pooled estimate was combined with data from the 2006 American Society of Health-System Pharmacists Annual Survey, the 2007 American Hospital Association Annual Survey, and the latter's 2008 Electronic Health Record Adoption Database supplement to estimate the percentage and absolute reduction in medication errors attributable to CPOE.

Results Processing a prescription drug order through a CPOE system decreases the likelihood of error on that order by 48% (95% CI 41% to 55%). Given this effect size, and the degree of CPOE adoption and use in hospitals in 2008, we estimate a 12.5% reduction in medication errors, or ~17.4 million medication errors averted in the USA in 1 year.

Discussion Our findings suggest that CPOE can substantially reduce the frequency of medication errors in inpatient acute-care settings; however, it is unclear whether this translates into reduced harm for patients.

Conclusions Despite CPOE systems' effectiveness at preventing medication errors, adoption and use in US hospitals remain modest. Current policies to increase CPOE adoption and use will likely prevent millions of additional medication errors each year. Further research is needed to better characterize links to patient harm.

which may further reduce errors. There is also some evidence that CPOE may cause errors.[5] CPOE's impact on medication errors and outcomes remains uncertain because of the varied clinical settings, CPOE system origins (commercial vs created in-house), and quality of existing studies.[6]

With its Healthcare Information Technology for Economic and Clinical Health (HITECH) provision, the American Recovery and Reinvestment Act of 2009 authorized US$20 billion in funding to assist in the development of a robust health information technology (health IT) infrastructure to improve healthcare safety and quality. Among the HITECH Act's provisions are incentive payments to outpatient physicians and hospitals to support health IT implementation, including CPOE implementation as a core requirement.[7]

The ultimate goal of CPOE is improved safety, quality, and value of patient care. Medication errors are an important intermediate, measurable outcome in pursuit of that goal. In this investigation, we examine the impact of CPOE on medication error frequency.

OBJECTIVE

The objective of this study was to provide a baseline national estimate of medication errors averted in hospitals due to use of CPOE, using data on CPOE use in 2008, before implementation of the HITECH Act. The baseline estimate and methodology may be useful to track national progress on CPOE adoption, use, and outcomes, and to inform the evolving federal strategy to build an effective health IT infrastructure.

MATERIALS AND METHODS

Example: Consumer informatics

TreatYoSelf: Empathy-driven behavioral intervention for marginalized youth living with HIV

Gabriela Marcu[1], Nadia Dowshen[2], Shuvadittya Saha[1], Ressa Reneth Sarreal[3], Nazanin Andalibi[1]

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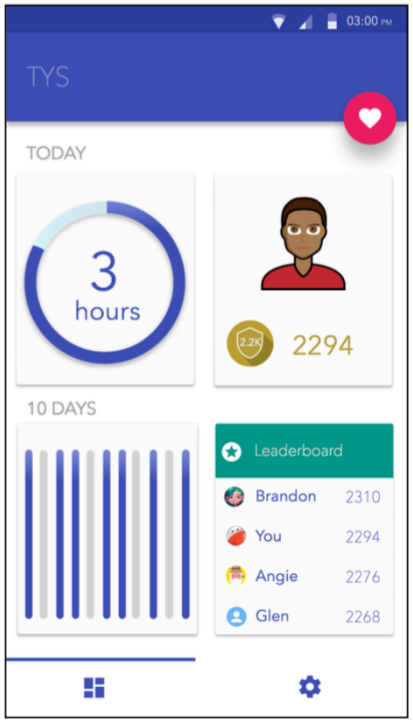
ABSTRACT

Behavioral intervention technologies are well suited to addressing health behavior such as medication adherence, but only if successfully integrated into a user's daily life. Little is known about how to design such technologies to be adoptable, adaptable, useful, and feasible in everyday life. We report on the design process for TreatYoSelf, a smartphone application designed to improve medication adherence among youth living with HIV through reminders and positive reinforcement. Using participatory design, our aim was to understand factors related to adoption and acceptance of behavioral intervention technology as part of daily life. Two challenges of living with HIV led to an empathy-driven approach in our design process: (1) HIV is a stigmatized condition, which (2) disproportionately affects the marginalized populations of young African American men who have sex with men and transgender women. We discuss five empathy-driven design strategies: positive and nonjudgmental tone; minimal, avatar-based gamification; motivational and corny messages; nondisclosure through neutral signifiers; and social support through camaraderie. Our approach enabled us to identify and work through factors, often related to stigma and marginalization, which would lead to rejection of TreatYoSelf use in daily life.



AMIA Themes

- **Biomedical Data Visualization**
- **Clinical Informatics:** findings related to the design, development, and implementation of state-of-the-art clinical systems
- **Clinical Research Informatics:** addressing the critical need for effective information management to address the many challenges facing clinical research
- **Clinical Workflow and Human Factors:** human factors aspects of clinical information system implementation and use that revolves around usability, workflow, and patient safety
- **Consumer Informatics and PHRs:** Personal Health Records (PHRs) and the consumer perspective in the use of health information science designed to improve patient engagement, medical outcomes, and the health care decision-making process
- **Mobile Health:** mHealth, Web 2.0, social media, telehealth/ telemedicine, and related topics
- **Data Interoperability and Information Exchange:** methods that organizations have undertaken to develop and implement various clinical data integration and exchange activities
- **Data Mining, NLP, Information Extraction Retrieval:** application of data mining, natural language processing, information extraction retrieval to all areas of biomedicine
- **Achieving Meaningful Use:** ways to promote the successful and effective development, implementation, and evaluation of Electronic Health Records as the nation works toward "meaningful use" of these systems
- **Global eHealth:** Global eHealth challenges
- **Informatics Education and Workforce Development:** effort to create a trained HIT workforce
- **Informatics in Health Professional Education:** application of information technology in health professional education
- **Interactive Systems:** human-computer interaction (HCI) research, compelling designs, or innovative interactive technologies
- **Policy and Ethical Issues:** unprecedented national HIT activity and ethical considerations posed as more practitioners and the public interface with these technologies.
- **Public Health Informatics and Biosurveillance:** disease detection, communications, workforce development, standards and interoperability, and best practices to combine the domains of health information science and technology with the practice and science of public health
- **Imaging Informatics:** intersection of imaging science, biomedical engineering and biomedical informatics,
- **Simulation and Modeling:** use of various computer-based simulation and modeling methodologies and tools as they can be applied within the field of biomedical informatics
- **Terminology and Standards Ontologies:** complex issues surrounding standard syntax, semantics, and pragmatics of design, development and use of various application-specific and general purpose clinical terminologies and ontologies
- **Translational Bioinformatics and Biomedicine:** opportunities in biomedical informatics that arise from the storage, retrieval, analysis, and dissemination of molecular and genomic information in a clinical setting context

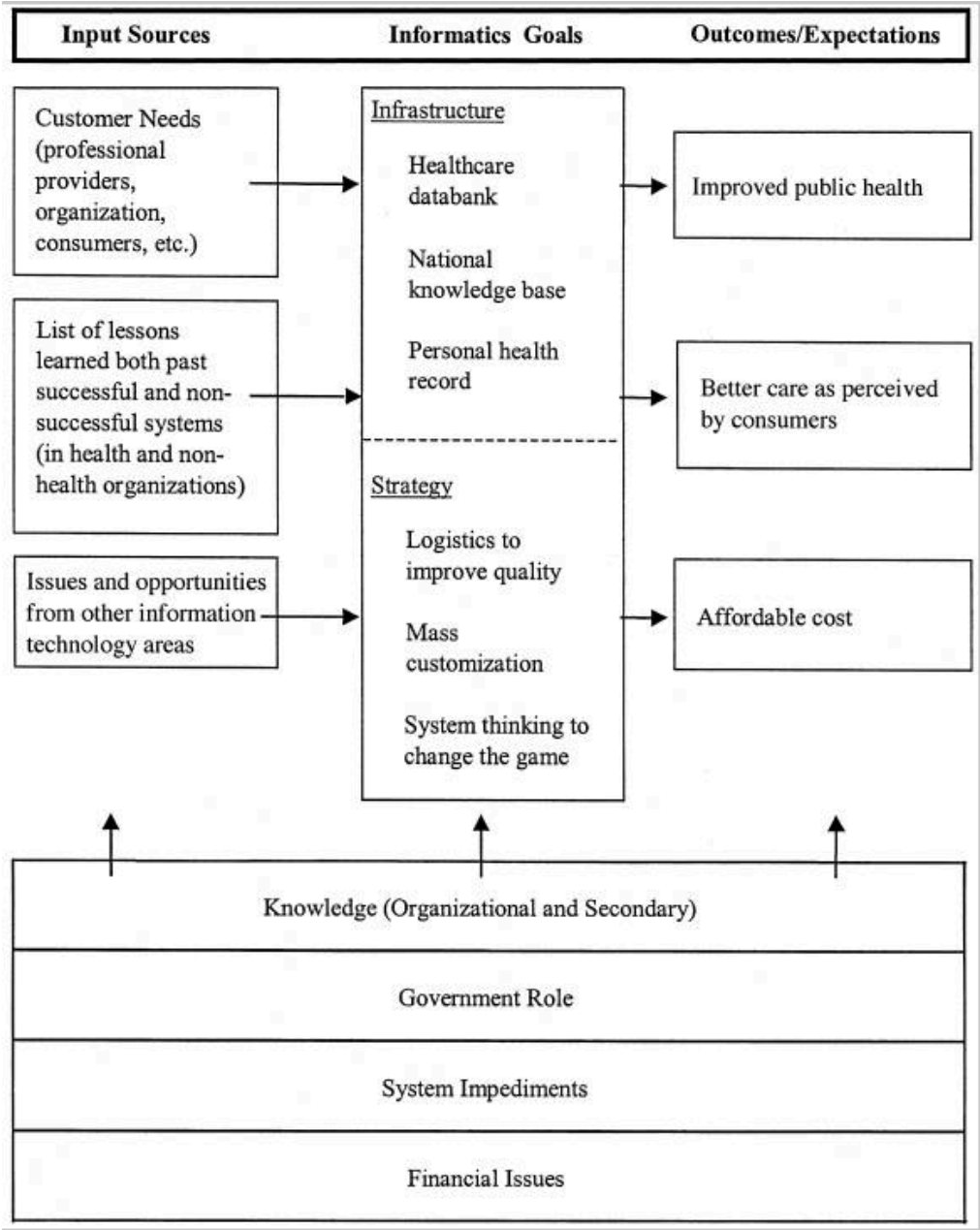
http://www.amia.org/amia2013/themes

Goals

Conceptual Value/Mission Model for Academic Health Centers

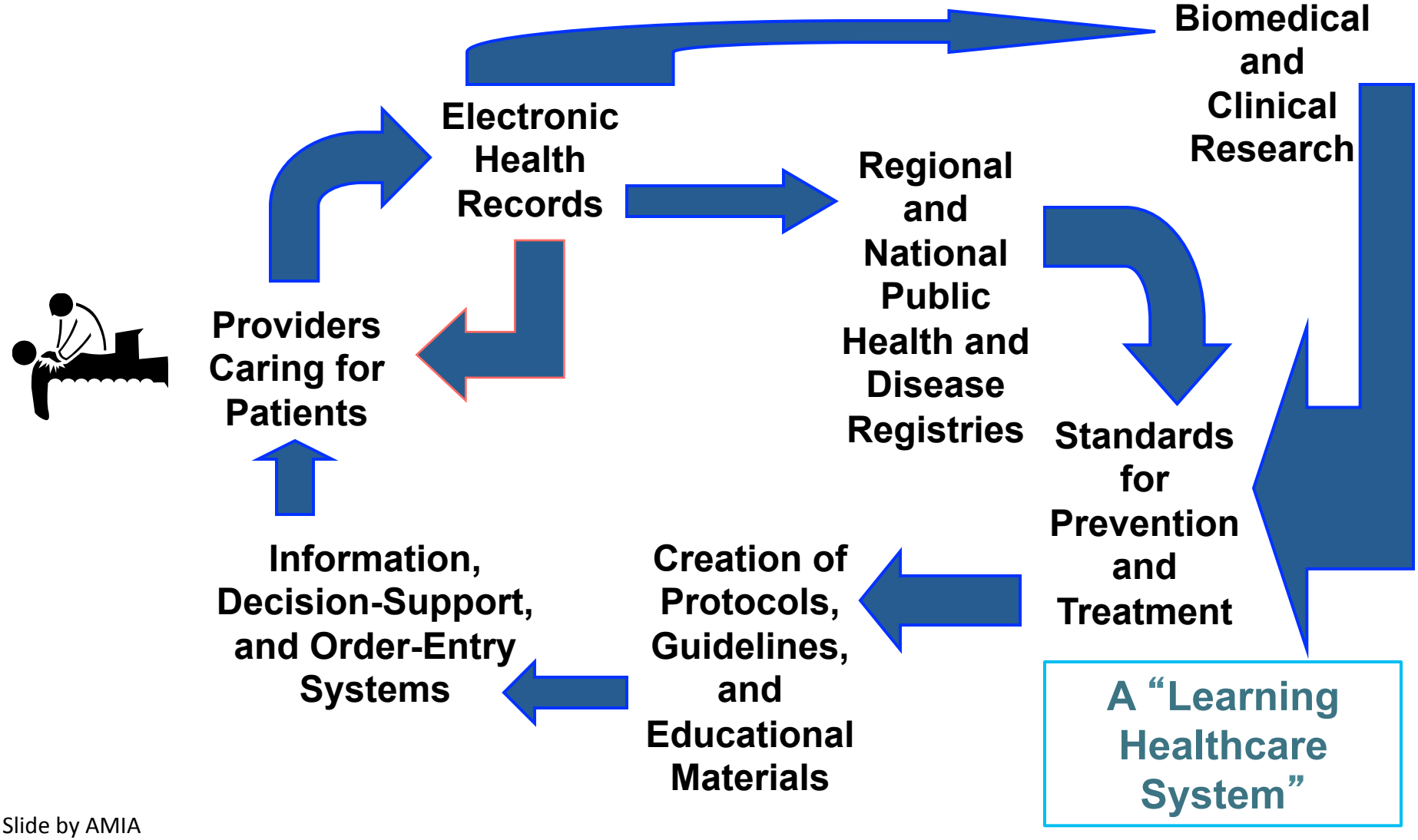
Value: Quality	Mission:		
	Patient Care	**Education**	**Research**
Right Thing (*Vision*)	■ Carriage trade ■ Individualization ■ Mass customization ■ Population-based medicine ■ Regional health model	■ Specialists ■ Family Practice Physicians ■ Academic Physicians ■ Allied Health Professionals	■ Advancing and communicating knowledge ■ Outcome research
Right Way (*Which, How*)	■ Traditional medicine ■ Complementary medicine ■ Evidence-based medicine ■ Standards of care ■ Practice guidelines ■ Protocols ■ Learning organization ■ Person empowerment ■ Shared responsibility	■ Lecture ■ Problem-based learning ■ Small group ■ Community-based learning ■ Apprenticeships	■ Laboratory-based research ■ Department/discipline ■ Interdisciplinary institutes ■ Academic health center
Right Time (*When*)	■ Acute care on demand ■ Preventive medicine ■ Public health education	■ Undergraduate medical education ■ Graduate medical education ■ AA/BA education ■ Just-in-time learning ■ Just-in-time training	■ Undergraduate education ■ Graduate education
Right Person (*Who*)	■ Physician ■ Integrated staff ■ Skill mix ■ Patient ■ Consumer/public	■ Physicians ■ Other faculty	■ Faculty ■ Interdisciplinary team

Stead, W.W. & Lorenzi, N.M., 1999, Health Informatics Linking Investment to Value, *Journal of the American Medical Informatics Association*, 6(5), pp. 341-8.



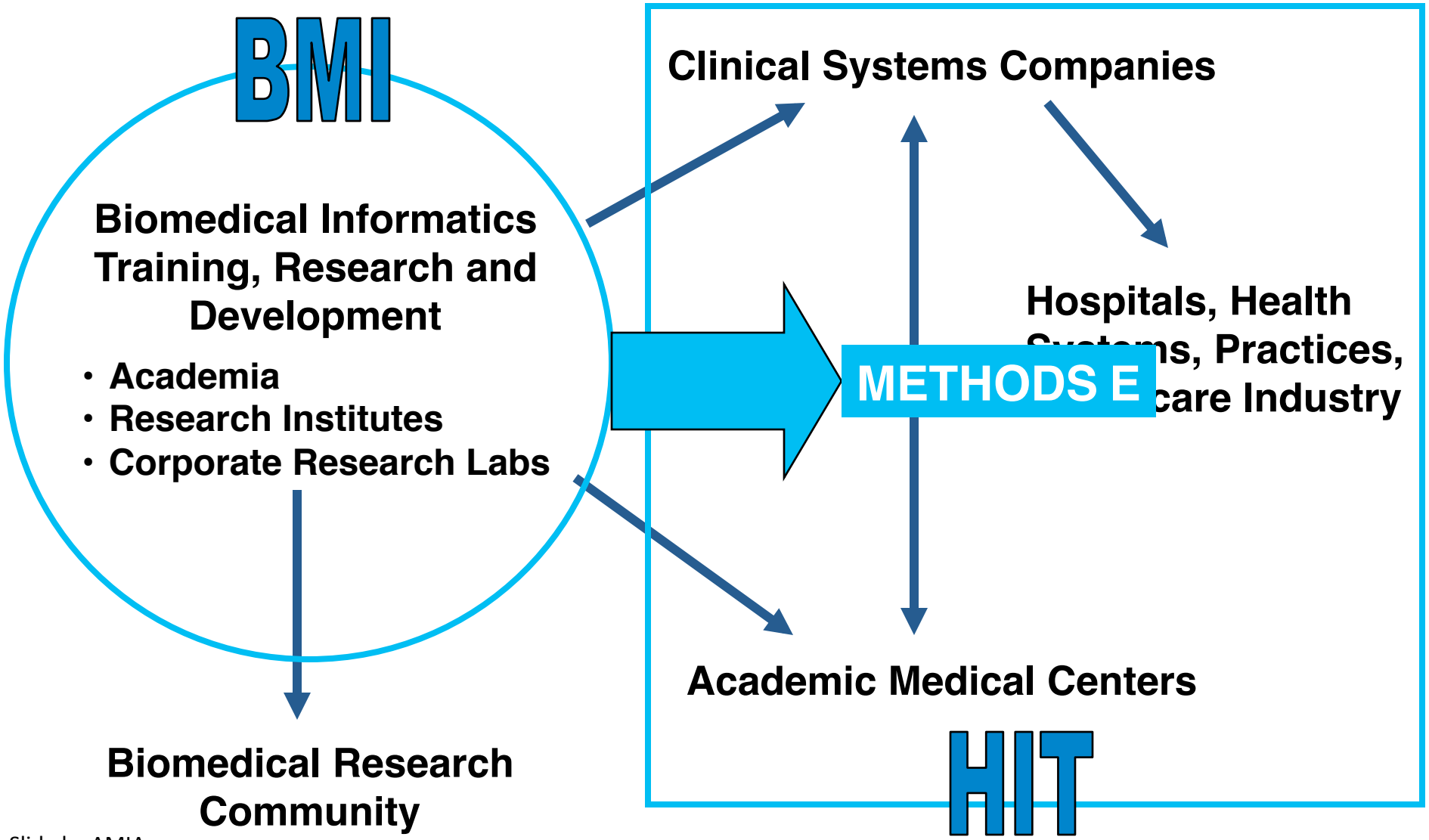
Stead, W.W. & Lorenzi, N.M., 1999, Health Informatics Linking Investment to Value, *Journal of the American Medical Informatics Association*, 6(5), pp. 341-8.

An Envisioned Cycle That Ties Patient Care with Knowledge Creation and Dissemination



Slide by AMIA

BMI and HIT



Slide by AMIA

Personalized medicine

Use individual level characteristics and information to tailor treatment

- Choosing between treatments vs. creating individual treatment

Personalized medicine + informatics

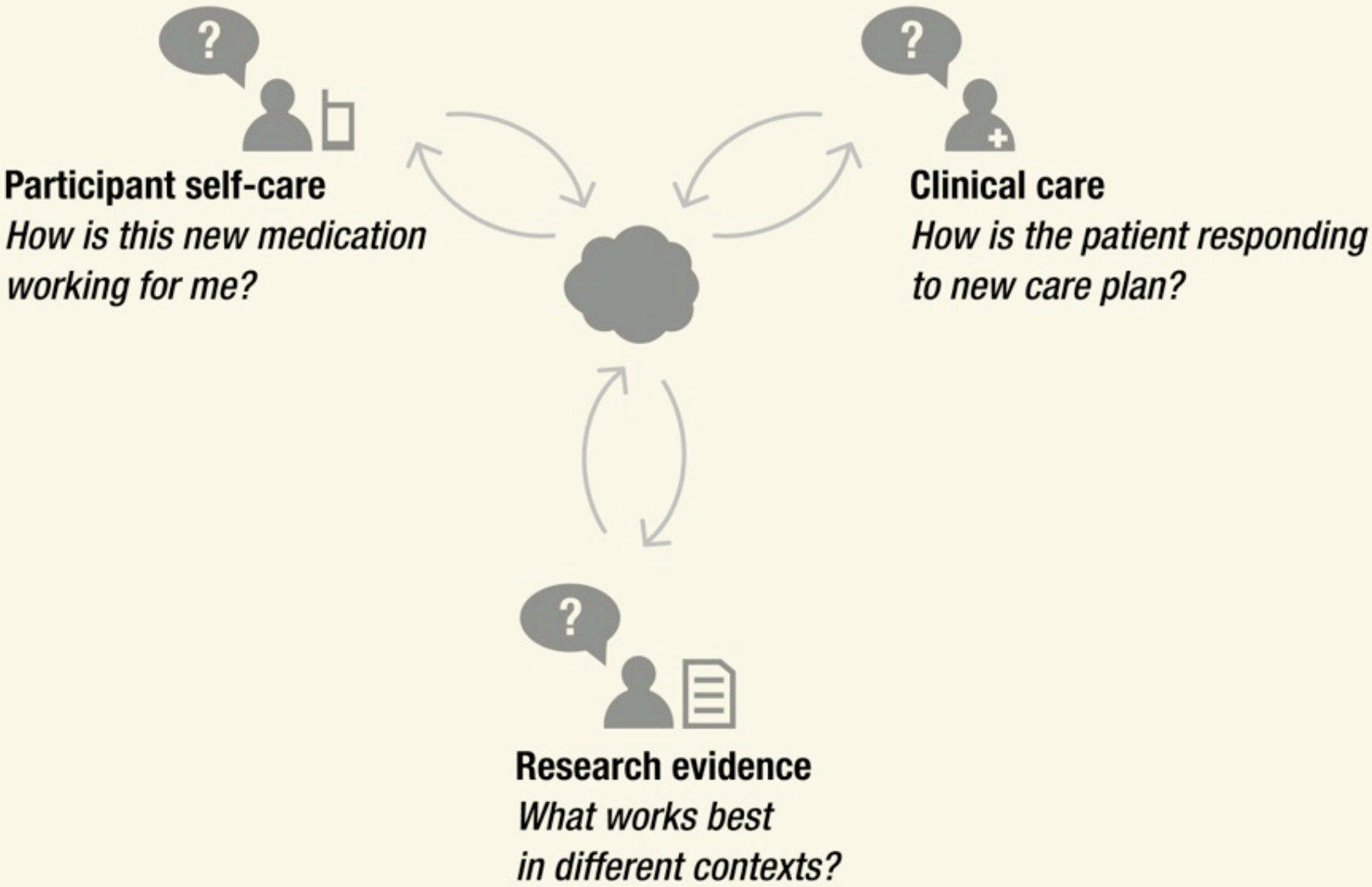
- Using -omics in clinical care
- Decision support
- Find similar patients – treatments, outcomes

Chronic disease

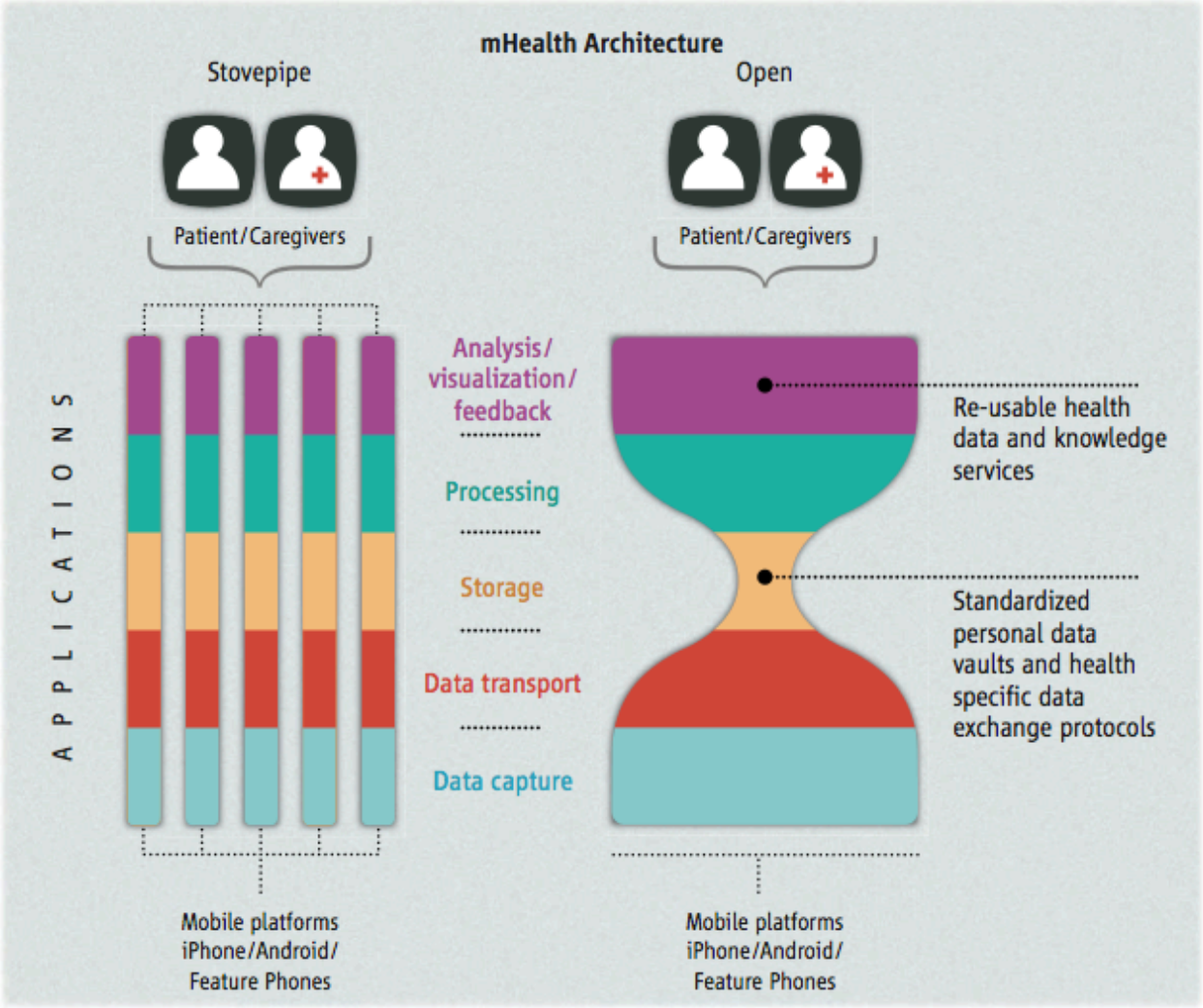
- Diabetes
- Obesity
- Asthma
- Epilepsy

…

Essential data driven feedback loops



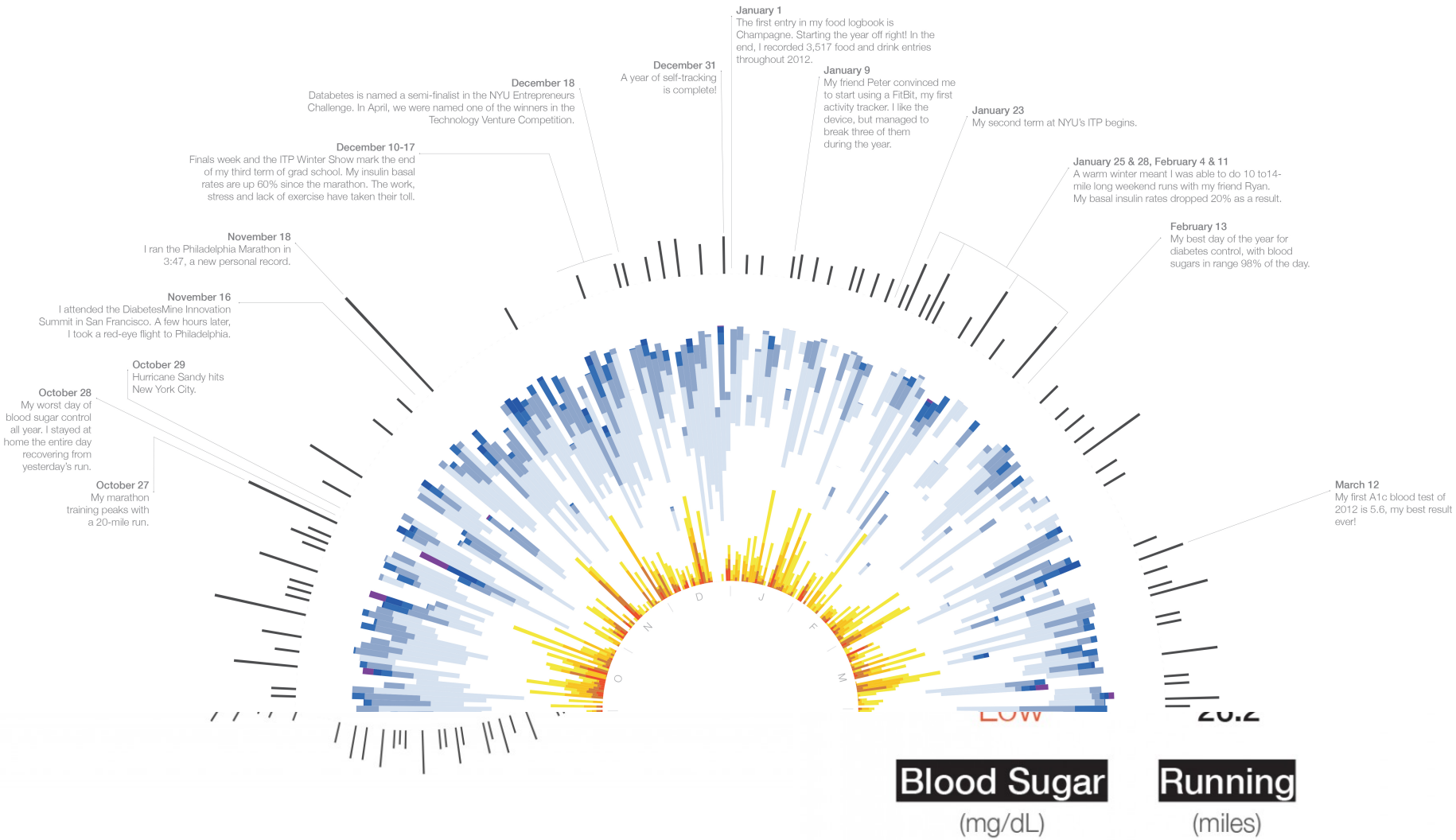
http://mobilizelabs.org/why-mhealth



mHealth architecture: Stovepipe versus Open. The narrow waist of the open hourglass will include at least health-specific syntactic and semantic data standards; patient identity standards; core data processing functions such as feature extraction and analytics; and data stores that allow for selective, patient-controlled sharing. Standards should be common with broader health IT standards whenever possible.

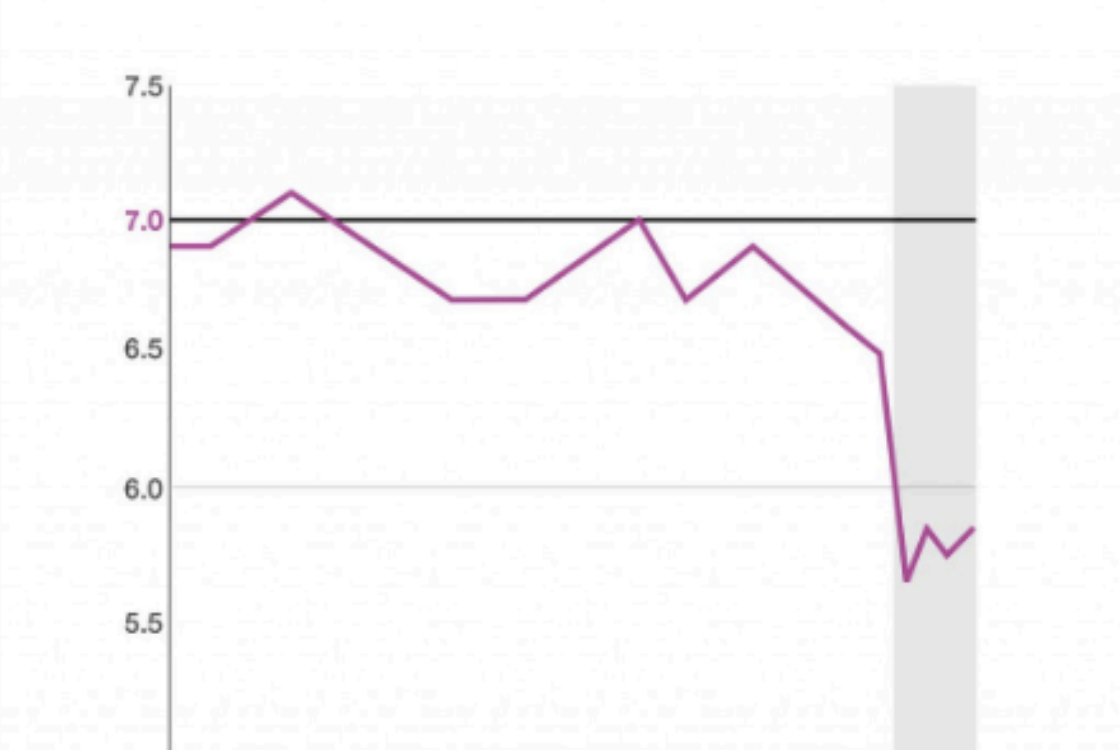
Estrin, D. & Sim, I., 2010, Open mHealth architecture: an engine for health care innovation, *Science(Washington)*, 330(6005), pp. 759-60

Quantified self



http://databetic.com

Self-tracking helped me achieve the best diabetes control of my life, as evident in my A1c results. This blood test is the standard metric for measuring diabetes control. The lower the reading the better. For context, I've included 10 years worth of my A1c readings.



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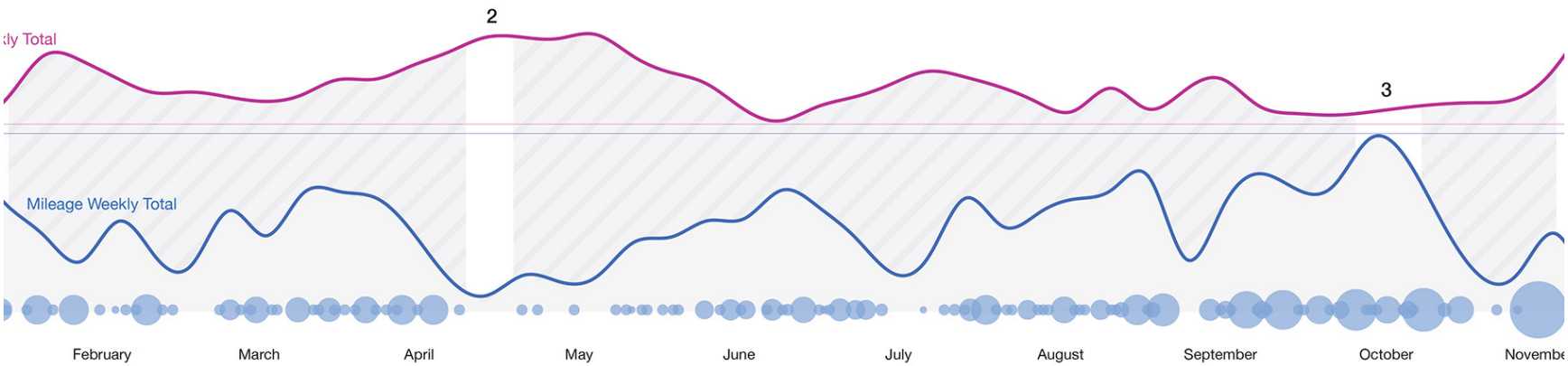
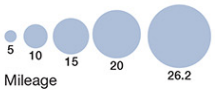




Exercise

Training for a Marathon

Most exercise lowers a patient's blood sugar right away. Frequent exercise can also lower overall insulin requirements.

In 2012, I trained for and ran the Philadelphia Marathon on November 18. During the year, I also had a few periods where I ran very little. These fluctuations translated into significant changes in my insulin levels throughout the year.

1 The winter was unusually warm. I began doing long weekend runs of 10-14 miles with my friend Ryan in late January. My insulin rates dropped about 20% as a result. For the rest of the spring, my insulin stayed steady.

2 At the end of my grad school term, my mileage dropped considerably. Insulin rates went up about 30% as a result.

Over the summer, I slowly got b
my insulin rates had dropped at
signed up for the Philadelphia M
July.

3 Marathon training peaked in late
at some of the lowest levels of t

4 By the time of the marathon, my
to rise because I was exercising
the race, my insulin rates rose a
I barely ran at all. It was also a b
end of my term at grad school,
requirements. Not until the holid
allowing my insulin rates to retu

http://databetic.com

Challenges/open problems

- Data
- Replication/validation
- Privacy/sharing
- Translation

Challenge: replication

Table 1: Reproducibility of research findings

Preclinical research generates many secondary publications, even when results cannot be reproduced.

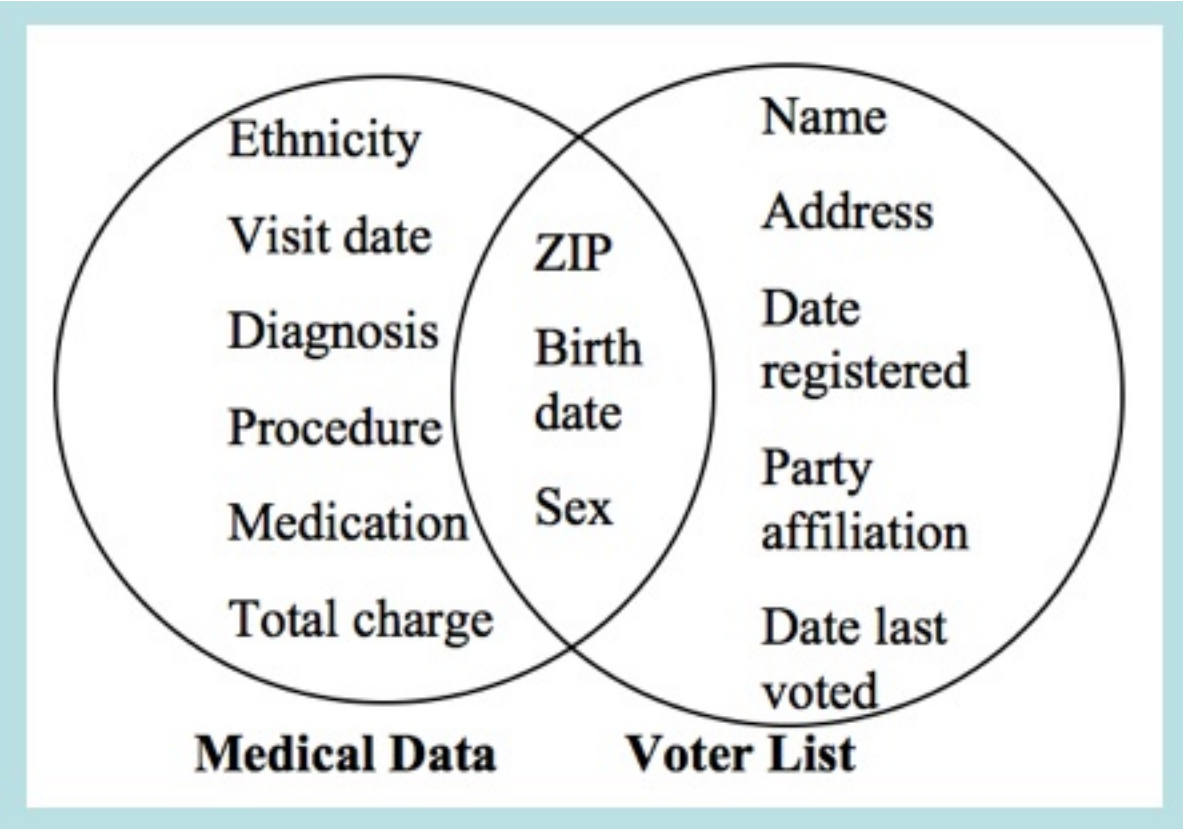
Journal impact factor	Number of articles	Mean number of citations of non-reproduced articles*	Mean number of citations of reproduced articles
>20	21	248 (range 3–800)	231 (range 82–519)
5–19	32	169 (range 6–1,909)	13 (range 3–24)

Results from ten-year retrospective analysis of experiments performed prospectively. The term 'non-reproduced' was assigned on the basis of findings not being sufficiently robust to drive a drug-development programme.

*Source of citations: Google Scholar, May 2011.

Drug development: Raise standards for preclinical cancer research
C. Glenn Begley & Lee M. Ellis
Nature 483, 531–533 (29 March 2012) doi: 10.1038/483531a

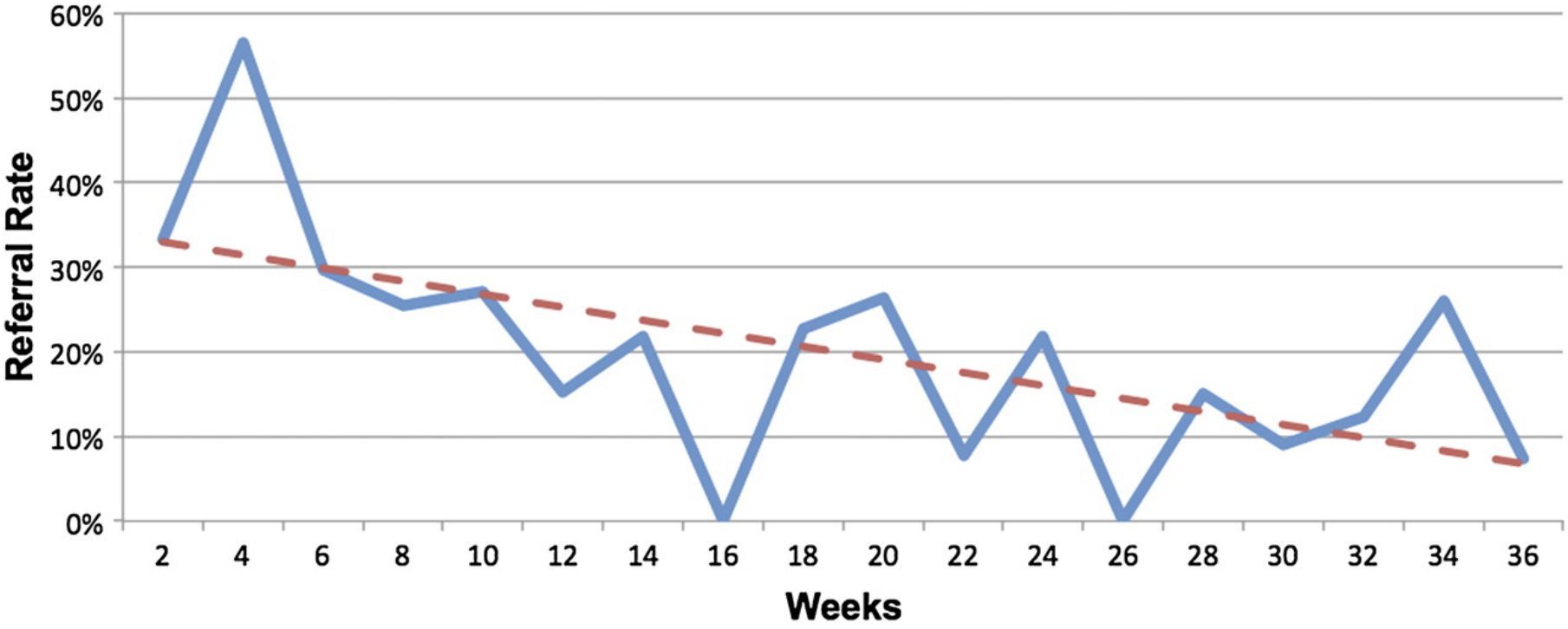
Challenge: Privacy



"87% of the U.S. Population are uniquely identified by {date of birth, gender, ZIP}."

http://latanyasweeney.org/work/identifiability.html

Challenge: Alert fatigue



Embi P J , and Leonard A C J Am Med Inform Assoc doi: 10.1136/amiajnl-2011-000743

For next week

- Be sure to read Wicks et al. paper in syllabus!
- Response due Friday by noon!